Event-triggered Fault Detection for Discrete-time LPV Systems

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***Abstract*—In this paper, a new event-triggering mechanism is proposed for the problem of fault detection (FD) in discrete-time linear parameter-varying (LPV) systems. A parameter-dependent event-based observer is designed as the residual generator, that only uses the sensor and scheduling variables data that are transmitted only when they are needed. Toward this goal, based on the concept of input-to-state stability, a new formulation is presented to satisfy the H_-/H_∞ performance measures and for each performance index, sufficient conditions are given in terms of linear matrix inequalities problems. It is shown that through two event-triggered data transmission mechanisms, the amount of data sent to the fault detection module is decreased significantly. Simulation results demonstrate the effectiveness of the proposed design methodology.**

***Index Terms*—Fault detection; Linear parameter-varying systems (LPV); Event-triggered observer; Input-to-state stability; Linear matrix inequality (LMI).**

I. Introduction

Model-based fault detection and isolation (FDI) for dynamic systems have been an important research area to ensure the safety and reliability and have attracted considerable attention during the last two decades [1]–[4]. The basic idea behind model-based FDI is to design filters or state observers to build a residual signal and then compare this signal with a predefined threshold. An alarm is generated when the residual evaluation function has a value larger than the threshold [5]. However, the performance of an FDI system can be degraded due to the effects of external disturbances. Hence, it is essential that the fault detection modules are designed to be sensitive to faults and, at the same time, robust to disturbances. The fault detection filter design has been formulated as an H_∞ filtering problem in [6], where error between the reference residual and the actual residual is minimized. The performance index H_- as a very appropriate measure to ensure a minimum sensitivity of the designed fault detection module to a fault has been used since the early 1990's [7]–[9]. In [10], a state space solution to the multi-objective H_-/H_∞ fault detection (FD) problem has been given for linear time-invariant (LTI) systems. The H_-/H_∞ performance indices have been used to minimize the sensitivity of the residual signal to disturbances while maintaining a minimum level of sensitivity to faults. The use of linear FDI methods can be extended to nonlinear systems through linearization around an operating point [11]. However, this approach is not successful for many dynamical systems since the highly nonlinear dynamics or large operating range may not allow a good linear approximation. Therefore, several new approaches have been developed to cope with the problem of FDI for nonlinear systems which can utilize the nonlinear models [12], neural networks [13] and Takagi-Sugeno (TS) fuzzy systems [14].

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As an alternative modeling approach, the linear parameter-varying (LPV) framework can be used to take advantage of the simplicity of LTI control synthesis methods and, at the same time, accurately capture the dynamics of nonlinear systems [15]. Recently, the FDI of LPV systems has become an attractive research area in the field of FDI [16]–[18]. In [18], a new stable FD observer design method has been proposed for LPV systems in a finite frequency domain. The H_- fault sensitivity condition in finite frequency domain is obtained by generalized Kalman-Yakubovich-Popov (KYP) lemma and the method of blocking matrix. Mixed H_-/H_∞ index framework has been considered in fault detection (FD) observer design for LPV systems in [19]. An FD observer under a mixed H_-/H_∞ framework for descriptor LPV systems has been presented in [20] in order to minimize the effect of disturbances and maximize the effect of faults on the residuals.

The advent of communication networks introduced the concept of networked control systems (NCS). The huge benefits of NCS including the low cost of installation, maintenance, and high reliability has resulted in considerable attention in this research field. However, utilizing communication network causes some challenging issues. Limited communication bandwidth can be considered as one of the most important restrictions in NCS. Therefore, it is a trend toward reduction of the data transmission in the design of control systems to minimize the bandwidth and energy consumption. Recently, a new approach called *event-triggered control* has been proposed, in which sensing and actuation are done only when they are necessary to maintain the desired operation. Event-triggering scheme can be employed to reduce the communication among sensors, control modules and actuators, and to significantly reduce the usage of communication resources compared with the implementation of periodic sampling in NCS. The original idea of event-based control was proposed in [21]. In the literature, several different event-triggering mechanisms and control strategies are presented (see, e.g., [22]–[28]). The benefits of event-triggering scheme can be capitalized on fault detection and isolation in NCS to reduce the data communication between sensors and fault detector modules. In [29], the event-based fault detection for the networked systems with communication delay and nonlinear perturbation has been investigated. An FD framework for networked control systems has been proposed in [30]. Then, the synthesis of FD filters under any event-triggering mechanism is investigated. Recently, the problem of event-triggered fault detection and isolation filter design for discrete-time LTI systems was addressed [31], [32] and the problem of event-triggered integrated fault detection, isolation and control (E-IFDIC) for discrete-time linear systems was investigated in [33]. Still, most of the prior results on the event-based schemes have been obtained for LTI or nonlinear models and only a few studies have focused on LPV systems [34], [35]. However, particularly, to the best of our knowledge, there is no study available on the event-triggered fault detection of LPV systems.

In this paper, a novel event-triggering scheme is proposed for the fault detection of discrete-time LPV systems to reduce the data transmission between the sensors or the scheduling variables and the FD module by designing two event generators. In fact, two event generator mechanisms are developed to separately send the sensors and the scheduling variables data to the FD module only when it is needed. The LMI conditions and event triggering conditions are obtained based on the concept of input-to-state stability. It is assumed that the LPV system is subjected to faults and external disturbances. Toward this goal, two performance indices of H_{-} and H_{∞} are considered in this study to assure the sensitivity of the fault detection module to the fault and its robustness to external disturbances, respectively. Therefore, the proposed strategy can be interpreted as a multi-objective problem since two different objectives must be satisfied simultaneously.

This paper is organized as follows. The problem statement is presented in Section II . The main results are given in Section III, where two event-triggering conditions and the procedure for designing the fault detection module for discrete-time LPV systems are addressed. In Section IV, properties and performance of the proposed design approaches are studied through a numerical example. The concluding remarks are given in Section V.

Notation: In this paper, $\mathbb{R}, \mathbb{R}^+$ and $\mathbb{Z}^+$ denote the set of real numbers, the set of nonnegative real numbers and the set of nonnegative integers, respectively. The i^{th} element of a real vector x is denoted by x^i (subscripts are used for denoting discrete time instants). We denote $||x||=\sqrt{x^\top x}$ and $||x||_2=\sqrt{\sum_{k=0}^{\infty}||x(k)||^2}$ for $x \in \mathbb{R}^n$. When a matrix P is positive definite (including symmetry), we write $P>0$. If it is positive semi-definite, we use $P \geq 0$. Similarly, for negative definiteness and negative semi-definiteness, we use $P<0$ and $P \leq 0$, respectively. By 0 and I, we denote the zero matrix and the identity matrix of appropriate dimensions, respectively. A star $(\star)$ in a matrix indicates a transposed quantity in the symmetric position. A function $\beta : \mathbb{R}^+ \to \mathbb{R}^+$ belongs to class $\mathcal{K}$ if it is continuous, strictly increasing and $\beta(0)=0$, and to class $\mathcal{K}_\infty$ if additionally $\beta(k) \to \infty$ as $k \to \infty$.

II. Problem Statement

Consider the discrete-time LPV system subjected to fault and disturbance in the form of

$$\begin{aligned} x(k+1) &= A(\theta_k)x(k) + B_1\omega(k) + B_2 f(k), \\ y(k) &= Cx(k) + D_1\omega(k) + D_2 f(k), \end{aligned} \tag{1}$$

with state $x(k) \in \mathbb{R}^{n_x}$, output $y(k) \in \mathbb{R}^{n_y}$, disturbance $\omega(k) \in \mathbb{R}^{n_\omega}$, fault $f(k) \in \mathbb{R}^{n_f}$, and $\theta_k \in \mathbb{R}^{n_\theta}$ as the scheduling variable vector. It is assumed that disturbance and fault signal are ℓ_2 norm bounded. The variable θ_k is assumed to lie in a compact set $\Theta \subset \mathbb{R}^{n_\theta}$ for all $k \in \mathbb{Z}^+$. It is assumed that an appropriate state or output feedback controller has been implemented to guarantee the stability of the system, and the residual generator is designed for the closed-loop systems. The system matrix $A(\theta_k) \in \mathbb{R}^{n_x \times n_x}$ is assumed to depend on θ_k and can be written in the polytopic form as

$$A(\theta_k) = \sum_{j=1}^{n} \eta_j(\theta_k) A_j, \tag{2}$$

where $\eta_j : \Theta \to \mathbb{R}$ and the mapping $\eta : \Theta \to \mathbb{R}^n$ given by $\eta := [\eta_1 \ldots \eta_n]^\top$ is such that $\eta(\Theta) \in \mathcal{S}$ with

$$\mathcal{S} = \{\mu \in \mathbb{R}^n | \mu_j \geq 0, j=1,\ldots,n \text{ and } \sum_{j=1}^{n} \mu_j = 1\}. \tag{3}$$

Hence, for instance $A(\theta_k)$ lies for each $\theta_k \in \Theta$ in the convex hull $\mathrm{Co}\{A_1,\ldots,A_n\}$ with n vertices. Note that, in this paper, we use the shorthand $\eta_j(\theta_k) := \eta_j(k)$.

Remark 1. *The systems matrix $A(\theta_k)$ in the LPV model (1) can be represented as follows*

$$A(\theta_k) = A^{(0)} + \sum_{l=1}^{n_\theta} \mathscr{F}_l(\theta_k^l) A^{(l)}, \tag{4}$$

where $A^{(l)}, l = 0,\ldots,n_\theta$, are constant matrices and $\mathscr{F}_l(\theta_k^l), l = 1,\ldots,n_\theta$ are assumed to be Lipschitz functions of the scheduling variables θ_k^l where $\theta_k^1,\ldots,\theta_k^{n_\theta}$ are the elements of the vector θ_k. Since each function $\mathscr{F}_l$ is assumed to be Lipschitz, there exists a constant ζ_l such that for all $\theta_k^l, \hat{\theta}_k^l \in \Theta$ we have

$$|\mathscr{F}_l(\theta_k^l) - \mathscr{F}_l(\hat{\theta}_k^l)| \leq \zeta_l |\theta_k^l - \hat{\theta}_k^l|. \tag{5}$$

In case of affine LPV systems, state matrix depends affinely on the parameter vector, and hence these functions can be represented as $\mathscr{F}_l(\theta_k^l) = \theta_k^l,\ l = 1, ..., n_\theta$. Later, in this paper, we use this representation to analyze the error $A(\theta_k) - A(\hat{\theta}_k)$.

The main concept of the event-triggered FD observer for LPV systems is depicted in Figure 1. In this setting, to detect an occurred fault, event generators are employed to determine time instants $k_i^y, k_s^\theta (i, s = 0, 1, 2, ...) \in \mathbb{Z}^+$, in which information of the sensors $(y(k_i^y))$ and the scheduling variable $(\hat{\theta}_k = \theta_{k_s^\theta})$ are sent to the FD filter. The proposed event-triggered framework is intended to reduce the data transmission of the scheduling variables and the output signals. To this aim, whenever a significant change occurs in the scheduling variables or the output signals, the information is sent to the FD filter in order to detect the occurred fault.

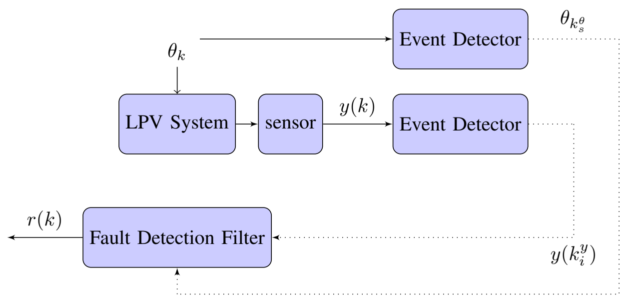

Fig. 1: The schematic of event-triggered FD approach for an LPV system.

III. MAIN RESULTS

In this section, a procedure is proposed for fault detection of LPV systems, where event-triggering conditions along with a parameter-dependent observer gain are designed such that the occurred fault can be detected while a performance criterion is satisfied. For the purpose of residual generation for the LPV system (1), the following event-triggered FD observer is proposed as

$$\begin{aligned} \hat{x}(k+1) &= A(\hat{\theta}_k)\hat{x}(k) + L(\hat{\theta}_k)\left(y(k_i^y) - \hat{y}(k)\right), \\ \hat{y}(k) &= C\hat{x}(k), \\ r(k) &= y(k_i^y) - \hat{y}(k), \end{aligned} \tag{6}$$

where the matrix $L(\hat{\theta}_k) = \sum_{j=1}^{n} \eta_j(\hat{\theta}_k) L_j$ denotes the observer gain to be designed, $\hat{x}(k) \in \mathbb{R}^{n_x}$ and $\hat{y}(k) \in \mathbb{R}^{n_y}$ represent the state estimate and output estimate, respectively, $r(k) \in \mathbb{R}^{n_y}$ is the residual signal, $y(k_i^y)$ denotes the last measurement that is transmitted from the sensor to the residual generation module, and $\hat{\theta}_k = \theta_{k_s^\theta}$ is the last scheduling variable sent to the residual generator module.

We define the estimation error as $e(k) = x(k) - \hat{x}(k)$, the output measurement error in the interval of $[k_i^y, k_{i+1}^y)$ as $e_y(k) = y(k_i^y) - y(k)$, and the scheduling variables error in the interval of $[k_s^\theta, k_{s+1}^\theta)$ as $e_\theta(k) = \hat{\theta}_k - \theta_k$. It is assumed that whenever a significant change between event generator scheduling variable $\hat{\theta}_k$ and the system scheduling variable θ_k reaches a chosen threshold δ_1, i.e., $||e_\theta(k)|| > \delta_1$ with $\delta_1 > 0$, a new sample of θ_k is sent through the network.

The closed-loop system can be represented as

$$\begin{aligned} e(k+1) &= x(k+1) - \hat{x}(k+1), \\ &= \left(A(\hat{\theta}_k) - L(\hat{\theta}_k)C\right) e(k) + \Delta_A(\theta_k, \hat{\theta}_k)x(k) + \\ &\left(B_1 - L(\hat{\theta}_k)D_1\right)\omega(k) + \left(B_2 - L(\hat{\theta}_k)D_2\right) f(k) \\ &- L(\hat{\theta}_k)e_y(k), \end{aligned}$$

where $\Delta_A(\theta_k, \hat{\theta}_k) = A(\theta_k) - A(\hat{\theta}_k)$. By defining the augmented signal $\psi(k) = \begin{bmatrix} e^\top(k) & x^\top(k) \end{bmatrix}^\top$ and considering (1), the following augmented LPV system representation is obtained

$$\begin{aligned} \psi(k+1) &= \breve{A}(\hat{\theta}_k)\psi(k) + \breve{B}_1(\hat{\theta}_k)\omega(k) + \breve{B}_2(\hat{\theta}_k)f(k) \\ &\quad + \breve{L}(\hat{\theta}_k)e_y(k), \\ r(k) &= \breve{C}_1\psi(k) + D_1\omega(k) + D_2 f(k) + e_y(k), \\ y(k) &= \breve{C}_2\psi(k) + D_1\omega(k) + D_2 f(k), \end{aligned} \tag{7}$$

where

$$\begin{aligned} \breve{A}(\hat{\theta}_k) &= \begin{bmatrix} A(\hat{\theta}_k) - L(\hat{\theta}_k)C & 0 \\ 0 & A(\hat{\theta}_k) \end{bmatrix} + \breve{\Delta}_A(\theta_k, \hat{\theta}_k), \\ \breve{B}_1(\hat{\theta}_k) &= \begin{bmatrix} B_1 - L(\hat{\theta}_k)D_1 \\ B_1 \end{bmatrix}, \breve{B}_2(\hat{\theta}_k) = \begin{bmatrix} B_2 - L(\hat{\theta}_k)D_2 \\ B_2 \end{bmatrix}, \\ \breve{L}(\hat{\theta}_k) &= \begin{bmatrix} -L(\hat{\theta}_k) \\ 0 \end{bmatrix}, \quad \breve{\Delta}_A(\theta_k, \hat{\theta}_k) = \begin{bmatrix} 0 & \Delta_A(\theta_k, \hat{\theta}_k) \\ 0 & \Delta_A(\theta_k, \hat{\theta}_k) \end{bmatrix}, \\ \breve{C}_1 &= \begin{bmatrix} C & 0 \end{bmatrix}, \breve{C}_2 = \begin{bmatrix} 0 & C \end{bmatrix}. \end{aligned}$$

An upper bound of $||\Delta_A(\theta_k, \hat{\theta}_k)||$ can be found as

$$\Delta_A^\top(\theta_k, \hat{\theta}_k)\Delta_A(\theta_k, \hat{\theta}_k) \leq \bar{\sigma}^2(\Delta_A(\theta_k, \hat{\theta}_k))I, \tag{8}$$

where $\bar{\sigma}$ denotes the maximum singular value. From (4), $\Delta_A(\theta_k, \hat{\theta}_k)$ can be written as

$$\Delta_A(\theta_k, \hat{\theta}_k) = \sum_{l=1}^{n_\theta} \left(\mathscr{F}_l(\theta_k^l) - \mathscr{F}_l(\hat{\theta}_k^l)\right) A^{(l)}. \tag{9}$$

Therefore, from (5), $||e_\theta(k)|| \leq \delta_1$ ($|\theta_k^l - \hat{\theta}_k^l| \leq \delta_1, l = 1, ..., n_\theta$) and the using fact that $\bar{\sigma}(\mathcal{X}_1 + \mathcal{X}_2) \leq \bar{\sigma}(\mathcal{X}_1) + \bar{\sigma}(\mathcal{X}_2)$ for matrices $\mathcal{X}_1$ and $\mathcal{X}_2$, it follows that

$$\bar{\sigma}\left(\Delta_A(\theta_k, \hat{\theta}_k)\right) \leq \delta_1 \sum_{l=1}^{n_\theta} \zeta_l \bar{\sigma}(A^{(l)}), \tag{10}$$

where $\zeta_l > 0$ is the Lipschitz constant of the function $\mathscr{F}_l(\theta_k^l)$. Hence an upper bound of $||\Delta_A(\theta_k, \hat{\theta}_k)||$ can be found as follows

$$\Delta_A^\top(\theta_k, \hat{\theta}_k)\Delta_A(\theta_k, \hat{\theta}_k) \leq (\delta_1 \sum_{l=1}^{n_\theta} \zeta_l \bar{\sigma}(A^{(l)}))^2 I_{n_x}. \tag{11}$$

In the following, the main results on the design of a fault detection observer for the LPV system (1) are given. However, first, the concept of ISS-Lyapunov function is reviewed for (7) with $f(k) = 0$ and $\omega(k) = 0$, $\forall k \in \mathbb{Z}^+$.

Definition 1. *A function $V:\mathbb{R}^{n_\psi}\times\mathbb{R}^{n_\theta}\to\mathbb{R}^+$ is an input-to-state stable (ISS)-Lyapunov function [36] for (7) ($n_\psi = 2n_x$) if there exist $\mathcal{K}_\infty$ function ρ_1 and ρ_2 such that for any $\hat{\theta}_k,\hat{\theta}_{k+1}\in\Theta$, $k\in\mathbb{Z}^+$*

$$\rho_1(||\psi(k)||)\le V(\psi(k),\hat{\theta}_k)\le\rho_2(||\psi(k)||), \tag{12}$$

and there exists a $\mathcal{K}_\infty$ function ϱ_1 and $\mathcal{K}$ function κ_1 which satisfy

$$\begin{aligned} V(\psi(k+1),\hat{\theta}_{k+1})-V(\psi(k),\hat{\theta}_k)\le\\ -\varrho_1(||\psi(k)||)+\kappa_1(||e_y(k)||). \end{aligned} \tag{13}$$

Considering a $\mathcal{K}_\infty$ function ϱ_2, it follows that $-\varrho_1(||\psi(k)||)-\varrho_2(||y(k)||)+\kappa_1(||e_y(k)||)\le-\varrho_1(||\psi(k)||)+\kappa_1(||e_y(k)||)$, and hence a sufficient condition to satisfy inequality (13) is as follows

$$\begin{aligned} V(\psi(k+1),\hat{\theta}_{k+1})-V(\psi(k),\hat{\theta}_k)\le\\ -\varrho_1(||\psi(k)||)-\varrho_2(||y(k)||)+\kappa_1(||e_y(k)||). \end{aligned} \tag{14}$$

From inequality (14), the system represented by (7) is asymptotically stable for any $e_y(k)$ that satisfy

$$\kappa_1(||e_y(k)||)<\varrho_2||y(k)||. \tag{15}$$

Consequently, the event instants, when such a violation happens, are defined iteratively by

$$\begin{aligned} k^y_{i+1}&=\min\left\{k>k^y_i\mid\kappa_1(||e_y(k)||)>\varrho_2(||y(k)||)\right\},\\ k^\theta_{s+1}&=\min\left\{k>k^\theta_s\mid(||e_\theta(k)||)>\delta_1\right\}, \end{aligned} \tag{16}$$

with $k^\theta_0=k^y_0=0$. Therefore, in order to assure the asymptotic stability of the closed-loop system with $\omega=0$ and $f=0$, the data $y(k)$ and θ_k should be sent to the filter whenever the inequalities in (16) are satisfied. Therefore, the problem under investigation is to design the fault detection module (6) for the LPV system (1) and the event instants (16) such that the augmented system (7) is stable, the effect of disturbance on the residual signal $r(k)$ is minimized, and the effect of fault on $r(k)$ is maximized. More specifically, we are to design the fault detector (6) and the event instants (16) such that the augmented system (7) is stable, and the following performance indices are satisfied:

i) $\sup_{f=0,||\omega||_2\neq0}\dfrac{||r||_2}{||\omega||_2}<\gamma_1$ (H_∞ performance)

ii) $\inf_{\omega=0,||f||_2\neq0}\dfrac{||r||_2}{||f||_2}>\beta$ (H_- performance)

The performance index (i) is used to attenuate the effect of the disturbance on the residual signal and the performance index (ii) is used to guarantee a minimum level of sensitivity of the residual to the fault signal.

A. H_∞ performance

The following theorem gives a sufficient condition for the design of the parameter-dependent observer gain $L(\hat{\theta}_k)$ and the event-triggering condition to stabilize the augmented system (7) with a guaranteed H_∞ performance.

Theorem 1. *The augmented system described by (7) with $\hat{\theta}_k\in\Theta$, $f(k)=0$ and $k\in\mathbb{Z}^+$ is stable and satisfies the performance index (i) while the data is transmitted to the residual generator at the event instants (16) if for a given scalar δ_1, there exist symmetric positive definite matrices $P_i\in\mathbb{R}^{n_\psi\times n_\psi}$, matrices $G_i\in\mathbb{R}^{n_\psi\times n_\psi}$, $\mathcal{G}_i\in\mathbb{R}^{n_\psi\times n_\psi}$ and positive scalars $\alpha_1,\alpha_2,\alpha_3,\epsilon_1,\gamma,\zeta_l$ such that*

$$\begin{bmatrix} \mathcal{W}_{(1,1)i}-\epsilon_1\mathscr{A} & -\breve{C}_1^\top & \mathcal{W}_{(1,3)} & \mathcal{W}_{(1,4)i} & 0\\ \star & \mathcal{W}_{(2,2)} & D_1 & \mathcal{W}_{(2,4)i} & 0\\ \star & \star & \mathcal{W}_{(3,3)} & \mathcal{W}_{(3,4)i} & 0\\ \star & \star & \star & \mathcal{W}_{(4,4)ij} & G_i\\ \star & \star & \star & \star & \epsilon_1 I_{n_\psi} \end{bmatrix}>0,$$
$$i,j=1,\ldots,n, \tag{17}$$

Moreover, the vertices of the observer gain are obtained from $L_i=G^{-1}_{(1,1)i}\mathcal{G}_i$, $i=1,\ldots,n$, where $\mathscr{A}=$ $\mathrm{diag}(0,2(\delta_1\sum_{l=1}^{n_\theta}\zeta_l\bar{\sigma}(A^{(l)}))^2I_{n_x})$ and

$$\begin{aligned} \mathcal{W}_{(1,1)i}&=P_i-\alpha_1I_{n_\psi}-\breve{C}_1^\top\breve{C}_1-\alpha_3\breve{C}_2^\top\breve{C}_2,\\ \mathcal{W}_{(1,3)}&=-\breve{C}_1^\top D_1-\alpha_3\breve{C}_2^\top D_1,\quad \mathcal{W}_{(2,2)}=(\alpha_2-1)I_{n_y},\\ \mathcal{W}_{(1,4)i}&=\begin{bmatrix} A_i^\top G^\top_{(1,1)i}-C^\top\mathcal{G}_i^\top & 0\\ A_i^\top G^\top_{(1,2)i} & A_i^\top G^\top_{(2,2)i}\end{bmatrix},\\ G_i&=\begin{bmatrix} G_{(1,1)i} & G_{(1,2)i}\\ 0 & G_{(2,2)i}\end{bmatrix},\quad \mathcal{W}_{(2,4)i}=\begin{bmatrix}-\mathcal{G}_i^\top & 0\end{bmatrix},\\ \mathcal{W}_{(3,3)}&=\gamma_1^2I_{n_\omega}-D_1^\top D_1-\alpha_3D_1^\top D_1,\\ \mathcal{W}_{(3,4)i}&=\begin{bmatrix}B_1^\top G^\top_{(1,1)i}-D_1^\top\mathcal{G}_i^\top+B_1^\top G^\top_{(1,2)i} & B_1^\top G^\top_{(2,2)i}\end{bmatrix}\\ \mathcal{W}_{(4,4)ij}&=G_i+G_i^\top-P_j,\quad \mathcal{G}_i=G_{(1,1)i}L_i. \end{aligned}$$

Proof. Assume that $\varrho_1(||\psi(k)||)=\alpha_1\psi^\top(k)\psi(k)$, $\kappa_1(||e_y(k)||)=\alpha_2e_y^\top(k)e_y(k)$, $\varrho_2(||y(k)||)=\alpha_3y^\top(k)y(k)$. Consider the Lyapunov function as $V(\psi(k),\hat{\theta}_k)=\psi^\top(k)P(\hat{\theta}_k)\psi(k)$. To ensure the H_∞ performance and the ISS condition w.r.t. $e_y(k)$, the following inequality should be satisfied

$$\begin{aligned} &V(\psi(k+1),\hat{\theta}_{k+1})-V(\psi(k),\hat{\theta}_k)<\\ &\quad-\alpha_1\psi^\top(k)\psi(k)-r^\top(k)r(k)+\\ &\quad\gamma^2\omega^\top(k)\omega(k)-\alpha_3y^\top(k)y(k)+\alpha_2e_y^\top(k)e_y(k), \end{aligned} \tag{18}$$

and it follows from (7) with $f=0$ that

$$\begin{aligned} &\Big(\breve{A}(\hat{\theta}_k)\psi(k)+\breve{B}_1(\hat{\theta}_k)\omega(k)+\breve{L}(\hat{\theta}_k)e_y(k)\Big)^\top P(\hat{\theta}_{k+1})\\ &\Big(\breve{A}(\hat{\theta}_k)\psi(k)+\breve{B}_1(\hat{\theta}_k)\omega(k)+\breve{L}(\hat{\theta}_k)e_y(k)\Big)\\ &-\psi^\top(k)P(\hat{\theta}_k)\psi(k)<-\alpha_1\psi^\top(k)\psi(k)-r^\top(k)r(k)+\\ &\quad\gamma^2\omega^\top(k)\omega(k)-\alpha_3y^\top(k)y(k)+\alpha_2e_y^\top(k)e_y(k). \end{aligned}$$

Substituting $r(k)$ and $y(k)$ from (7), the above inequality can be rewritten as

$$\begin{bmatrix}\psi^\top(k) & e_y^\top(k) & \omega^\top(k)\end{bmatrix}W(\hat{\theta}_k,\vartheta_k)\begin{bmatrix}\psi(k)\\ e_y(k)\\ \omega(k)\end{bmatrix}>0, \tag{19}$$

where $\vartheta_k = \hat{\theta}_{k+1}$ and $\eta(\vartheta_k) \in \mathcal{S}$ in (3) and

$$W(\hat{\theta}_k, \vartheta_k) = \begin{bmatrix} W_{11} & W_{12} & W_{13} \\ \star & W_{22} & W_{23} \\ \star & \star & W_{33} \end{bmatrix},$$

with

$$\begin{aligned} W_{11} &= P(\hat{\theta}_k) - \alpha_1 I_{n_\psi} - \breve{A}^\top(\hat{\theta}_k) P(\vartheta_k) \breve{A}(\hat{\theta}_k) \\ &\quad - \breve{C}_1^\top \breve{C}_1 - \alpha_3 \breve{C}_2^\top \breve{C}_2, \\ W_{12} &= -\breve{A}^\top(\hat{\theta}_k) P(\vartheta_k) \breve{L}(\hat{\theta}_k) - \breve{C}_1^\top, \\ W_{13} &= -\breve{A}^\top(\hat{\theta}_k) P(\vartheta_k) \breve{B}_1(\hat{\theta}_k) - \breve{C}_1^\top D_1 - \alpha_3 \breve{C}_2^\top D_1, \\ W_{22} &= \mathcal{W}_{(2,2)} - \breve{L}^\top(\hat{\theta}_k) P(\vartheta_k) \breve{L}(\hat{\theta}_k), \\ W_{23} &= -\breve{L}^\top(\hat{\theta}_k) P(\vartheta_k) \breve{B}_1(\hat{\theta}_k) - D_1, \\ W_{33} &= \gamma_1^2 I_{n_\omega} - \breve{B}_1^\top(\hat{\theta}_k) P(\vartheta_k) \breve{B}_1(\hat{\theta}_k) \\ &\quad - D_1^\top D_1 - \alpha_3 D_1^\top D_1. \end{aligned}$$

The inequality (19) is equivalent to $M(\hat{\theta}_k, \vartheta_k) > 0$ and hence

$$\begin{bmatrix} \mathcal{W}_{(1,1)}(\hat{\theta}_k) & -\breve{C}_1^\top & \mathcal{W}_{(1,3)} \\ \star & \mathcal{W}_{(2,2)} & D_1 \\ \star & \star & \mathcal{W}_{(3,3)} \end{bmatrix} - \begin{bmatrix} \breve{A}^\top(\hat{\theta}_k) \\ \breve{L}^\top(\hat{\theta}_k) \\ \breve{B}_1^\top(\hat{\theta}_k) \end{bmatrix} P(\vartheta_k) \begin{bmatrix} \breve{A}(\hat{\theta}_k) & \breve{L}(\hat{\theta}_k) & \breve{B}_1(\hat{\theta}_k) \end{bmatrix} > 0, \quad (20)$$

with

$$\begin{aligned} \mathcal{W}_{(1,1)}(\hat{\theta}_k) &= P(\hat{\theta}_k) - \alpha_1 I_{n_\psi} - \breve{C}_1^\top \breve{C}_1 - \alpha_3 \breve{C}_2^\top \breve{C}_2, \\ \mathcal{W}_{(1,3)} &= -\breve{C}_1^\top D_1 - \alpha_3 \breve{C}_2^\top D_1, \; \mathcal{W}_{(2,2)} = (\alpha_2 - 1) I_{n_y}, \\ \mathcal{W}_{(3,3)} &= \gamma_1^2 I_{n_\omega} - D_1^\top D_1 - \alpha_3 D_1^\top D_1. \end{aligned}$$

and by using Schur complement [37], it follows that

$$\begin{bmatrix} \mathcal{W}_{(1,1)}(\hat{\theta}_k) & -\breve{C}_1^\top & \mathcal{W}_{(1,3)} & \breve{A}^\top(\hat{\theta}_k) \\ \star & \mathcal{W}_{(2,2)} & D_1 & \breve{L}^\top(\hat{\theta}_k) \\ \star & \star & \mathcal{W}_{(3,3)} & \breve{B}_1^\top(\hat{\theta}_k) \\ \star & \star & \star & P^{-1}(\vartheta_k) \end{bmatrix} > 0. \quad (21)$$

Multiplying (21) by $\operatorname{diag}\Big(I, I, I, G(\hat{\theta}_k)\Big)$ from left and by $\operatorname{diag}\Big(I, I, I, G^\top(\hat{\theta}_k)\Big)$ from right, where $G(\hat{\theta}_k)$ is an invertible matrix with appropriate dimension written in the polytopic form as

$$\begin{aligned} G(\hat{\theta}_k) &= \begin{bmatrix} G_{(1,1)}(\hat{\theta}_k) & G_{(1,2)}(\hat{\theta}_k) \\ 0 & G_{(2,2)}(\hat{\theta}_k) \end{bmatrix} \\ &= \sum_{i=1}^{n} \eta_i(\hat{\theta}_k) \begin{bmatrix} G_{(1,1)i} & G_{(1,2)i} \\ 0 & G_{(2,2)i} \end{bmatrix}, \end{aligned} \quad (22)$$

it follows that

$$\begin{bmatrix} \mathcal{W}_{(1,1)}(\hat{\theta}_k) & -\breve{C}_1^\top & \mathcal{W}_{(1,3)} & \breve{A}^\top(\hat{\theta}_k) G^\top(\hat{\theta}_k) \\ \star & \mathcal{W}_{(2,2)} & D_1 & \breve{L}^\top(\hat{\theta}_k) G^\top(\hat{\theta}_k) \\ \star & \star & \mathcal{W}_{(3,3)} & \breve{B}_1^\top(\hat{\theta}_k) G^\top(\hat{\theta}_k) \\ \star & \star & \star & G(\hat{\theta}_k) P^{-1}(\vartheta_k) G^\top(\hat{\theta}_k) \end{bmatrix} > 0. \quad (23)$$

Since $\Big(P^{-1/2}(\vartheta_k) G^\top(\hat{\theta}_k) - P^{1/2}(\vartheta_k)\Big)^\top \Big(P^{-1/2}(\vartheta_k) G^\top(\hat{\theta}_k) - P^{1/2}(\vartheta_k)\Big) \geq 0$, it follows that

$$G(\hat{\theta}_k) P^{-1}(\vartheta_k) G^\top(\hat{\theta}_k) \geq G(\hat{\theta}_k) + G^\top(\hat{\theta}_k) - P(\vartheta_k). \quad (24)$$

Then, the inequality (23) can be written as

$$\begin{aligned} &\begin{bmatrix} \mathcal{W}_{(1,1)}(\hat{\theta}_k) & -\breve{C}_1^\top & \mathcal{W}_{(1,3)} & \mathcal{W}_{(1,4)}(\hat{\theta}_k) \\ \star & \mathcal{W}_{(2,2)} & D_1 & \mathcal{W}_{(2,4)}(\hat{\theta}_k) \\ \star & \star & \mathcal{W}_{(3,3)} & \mathcal{W}_{(3,4)}(\hat{\theta}_k) \\ \star & \star & \star & \mathcal{W}_{(4,4)}(\hat{\theta}_k, \vartheta_k) \end{bmatrix} + \\ &M_\Delta^\top(\hat{\theta}_k, \theta_k) M_G(\hat{\theta}_k) + M_G^\top(\hat{\theta}_k) M_\Delta(\hat{\theta}_k, \theta_k) > 0, \end{aligned} \quad (25)$$

where

$$\begin{aligned} \mathcal{W}_{(1,4)}(\hat{\theta}_k) &= \begin{bmatrix} \bar{\mathcal{W}}_{(1,4)} & 0 \\ A^\top(\hat{\theta}_k) G_{(1,2)}^\top(\hat{\theta}_k) & A^\top(\hat{\theta}_k) G_{(2,2)}^\top(\hat{\theta}_k) \end{bmatrix}, \\ \bar{\mathcal{W}}_{(1,4)} &= A^\top(\hat{\theta}_k) G_{(1,1)}^\top(\hat{\theta}_k) - C^\top \mathcal{G}^\top(\hat{\theta}_k), \\ \mathcal{W}_{(2,4)}(\hat{\theta}_k) &= \begin{bmatrix} -\mathcal{G}^\top(\hat{\theta}_k) & 0 \end{bmatrix}, \mathcal{G}(\hat{\theta}_k) = G_{(1,1)}(\hat{\theta}_k) L(\hat{\theta}_k), \\ \mathcal{W}_{(3,4)}(\hat{\theta}_k) &= \begin{bmatrix} \bar{\mathcal{W}}_{(3,4)}(\hat{\theta}_k) & B_1^\top G_{(2,2)}^\top(\hat{\theta}_k) \end{bmatrix}, \\ \bar{\mathcal{W}}_{(3,4)}(\hat{\theta}_k) &= B_1^\top G_{(1,1)}^\top(\hat{\theta}_k) - D_1^\top \mathcal{G}^\top(\hat{\theta}_k) \\ &\quad + B_1^\top G_{(1,2)}^\top(\hat{\theta}_k), \\ \mathcal{W}_{(4,4)}(\hat{\theta}_k, \vartheta_k) &= G(\hat{\theta}_k) + G^\top(\hat{\theta}_k) - P(\vartheta_k), \\ M_\Delta(\hat{\theta}_k, \theta_k) &= \begin{bmatrix} \breve{\Delta}_A(\hat{\theta}_k, \theta_k) & 0 & 0 & 0 \end{bmatrix}, \\ M_G(\hat{\theta}_k) &= \begin{bmatrix} 0 & 0 & 0 & G^\top(\hat{\theta}_k) \end{bmatrix}. \end{aligned}$$

Since

$$\Big(\epsilon_1 M_\Delta(\hat{\theta}_k, \theta_k) + M_G(\hat{\theta}_k)\Big)^\top \Big(\epsilon_1 M_\Delta(\hat{\theta}_k, \theta_k) + M_G(\hat{\theta}_k)\Big) \geq 0$$

with a positive scaler ϵ_1 it follows that

$$\begin{aligned} &M_\Delta^\top(\hat{\theta}_k, \theta_k) M_G(\hat{\theta}_k) + M_G^\top(\hat{\theta}_k) M_\Delta(\hat{\theta}_k, \theta_k) \geq \\ &-\epsilon_1 M_\Delta^\top(\hat{\theta}_k, \theta_k) M_\Delta(\hat{\theta}_k, \theta_k) - \epsilon_1^{-1} M_G^\top(\hat{\theta}_k) M_G(\hat{\theta}_k). \end{aligned} \quad (26)$$

Therefore, the inequality (25) is satisfied if

$$\begin{aligned} &\begin{bmatrix} \mathcal{W}_{(1,1)}(\hat{\theta}_k) & -\breve{C}_1^\top & \mathcal{W}_{(1,3)} & \mathcal{W}_{(1,4)}(\hat{\theta}_k) \\ \star & \mathcal{W}_{(2,2)} & D_1 & \mathcal{W}_{(2,4)}(\hat{\theta}_k) \\ \star & \star & \mathcal{W}_{(3,3)} & \mathcal{W}_{(3,4)}(\hat{\theta}_k) \\ \star & \star & \star & \mathcal{W}_{(4,4)}(\hat{\theta}_k, \vartheta_k) \end{bmatrix} \\ &- \epsilon_1 M_\Delta^\top(\hat{\theta}_k, \theta_k) M_\Delta(\hat{\theta}_k, \theta_k) - \epsilon_1^{-1} M_G^\top(\hat{\theta}_k) M_G(\hat{\theta}_k) > 0. \end{aligned} \quad (27)$$

From inequality (11) and using Schur complement, the above inequality is satisfied if

$$\left[\begin{array}{c|cccc} \begin{matrix} \mathcal{W}_{(1,1)}(\hat{\theta}_k) \\ -\epsilon_1 \mathscr{A} \end{matrix} & -\breve{C}_1^\top & \mathcal{W}_{(1,3)} & \mathcal{W}_{(1,4)}(\hat{\theta}_k) & 0 \\ \hline \star & \mathcal{W}_{(2,2)} & D_1 & \mathcal{W}_{(2,4)}(\hat{\theta}_k) & 0 \\ \star & \star & \mathcal{W}_{(3,3)} & \mathcal{W}_{(3,4)}(\hat{\theta}_k) & 0 \\ \star & \star & \star & \mathcal{W}_{(4,4)}(\hat{\theta}_k, \vartheta_k) & G(\hat{\theta}_k) \\ \star & \star & \star & \star & \epsilon_1 I_{n_\psi} \end{array}\right] > 0, \quad (28)$$

where $\mathscr{A} = \mathrm{diag}(0, 2(\delta_1 \sum_{l=1}^{n_\theta} \zeta_l \bar{\sigma}(A^{(l)}))^2 I_{n_x})$. Now, using (2) and (3), inequality (17) can be directly obtained from (28) and hence the proof is completed. $\square$

Remark 2. *In case of affine LPV systems, we have $\zeta_l = 1$, $l = 1, \ldots, n_\theta$, and hence, from (11) the upper bound for $\bar{\sigma}\left(\Delta_A(\theta_k, \hat{\theta}_k)\right)$ can be obtained as follows*

$$\bar{\sigma}\left(\Delta_A(\theta_k, \hat{\theta}_k)\right) \leq \delta_1 \sum_{l=1}^{n_\theta} \bar{\sigma}(A^{(l)}). \tag{29}$$

B. H_- performance

The following theorem gives the LMI conditions to ensure that the performance index (ii) is met.

Theorem 2. *Consider the augmented system described by (7) with $\hat{\theta}_k \in \Theta$, $\omega(k) = 0$ and $k \in \mathbb{Z}^+$. The performance index (ii) is satisfied with the data transmitted to the residual generator at the event instants (16) if for a given scalar δ_1, there exist symmetric positive definite matrices $P_i^{'} \in \mathbb{R}^{n_\psi \times n_\psi}$, matrices $G_i^{'} \in \mathbb{R}^{n_\psi \times n_\psi}$, $\mathcal{G}_i \in \mathbb{R}^{n_\psi \times n_\psi}$ and positive scalars $\alpha_1, \alpha_2, \alpha_3, \epsilon_2, \beta, \zeta_l$ such that*

$$\begin{bmatrix} \mathcal{H}_{(1,1)i} - \epsilon_2 \mathscr{A} & \breve{C}_1^\top & \mathcal{H}_{(1,3)} & \mathcal{H}_{(1,4)i} & 0 \\ \star & \mathcal{H}_{(2,2)} & D_2 & \mathcal{H}_{(2,4)i} & 0 \\ \star & \star & \mathcal{H}_{(3,3)} & \mathcal{H}_{(3,4)i} & 0 \\ \star & \star & \star & \mathcal{H}_{(4,4)ij} & G_i^{'} \\ \star & \star & \star & \star & \epsilon_2 I_{n_\psi} \end{bmatrix} > 0,$$
$$i, j = 1, \ldots, n, \tag{30}$$

Moreover, the vertices of the observer gain are obtained from $L_i = G_{(1,1)i}^{-1} \mathcal{G}_i$, $i = 1, \ldots, n$, where $\mathscr{A} = \mathrm{diag}(0, 2(\delta_1 \sum_{l=1}^{n_\theta} \zeta_l \bar{\sigma}(A^{(l)}))^2 I_{n_x})$ and

$$\mathcal{H}_{(1,1)i} = P_i^{'} - \alpha_1 I_{n_\psi} + \breve{C}_1^\top \breve{C}_1 - \alpha_3 \breve{C}_2^\top \breve{C}_2,$$
$$\mathcal{H}_{(1,3)} = \breve{C}_1^\top D_2 - \alpha_3 \breve{C}_2^\top D_2, \quad \mathcal{H}_{(2,2)} = (\alpha_2 + 1) I_{n_y},$$
$$\mathcal{H}_{(1,4)i} = \begin{bmatrix} A_i^\top G_{(1,1)i}^\top - C^\top \mathcal{G}_i^\top & 0 \\ A_i^\top G_{(1,2)i}^{'\top} & A_i^\top G_{(2,2)i}^{'\top} \end{bmatrix},$$
$$G_i^{'} = \begin{bmatrix} G_{(1,1)i} & G_{(1,2)i}^{'} \\ 0 & G_{(2,2)i}^{'} \end{bmatrix}, \mathcal{H}_{(2,4)i} = \begin{bmatrix} -\mathcal{G}_i^\top & 0 \end{bmatrix},$$
$$\mathcal{H}_{(3,3)} = -\beta^2 I_{n_f} + D_2^\top D_2 - \alpha_3 D_2^\top D_2,$$
$$\mathcal{H}_{(3,4)i} = \left[B_2^\top G_{(1,1)i}^\top - D_2^\top \mathcal{G}_i^\top + B_2^\top G_{(1,2)i}^{'\top} \; B_2^\top G_{(2,2)i}^{'\top} \right],$$
$$\mathcal{H}_{(4,4)ij} = G_i^{'} + G_i^{'\top} - P_j^{'}, \quad \mathcal{G}_i = G_{(1,1)i} L_i.$$

Proof. Consider the Lyapunov function $V(\psi(k), \hat{\theta}_k) = \psi^\top(k) P'(\hat{\theta}_k) \psi(k)$. To ensure the H_- performance, the following inequality should be satisfied

$$\begin{aligned} &V(\psi(k+1), \hat{\theta}_{k+1}) - V(\psi(k), \hat{\theta}_k) < \\ &\quad - \alpha_1 \psi^\top(k) \psi(k) + r^\top(k) r(k) - \\ &\quad \beta^2 f^\top(k) f(k) - \alpha_3 y^\top(k) y(k) + \alpha_2 e_y^\top(k) e_y(k). \end{aligned} \tag{31}$$

The rest of the proof is similar to that of Theorem 1 and is omitted for the sake of brevity. $\square$

In order to simultaneously guarantee the stability of the augmented system and the performance indices (i) and (ii), the following algorithm can be employed to design the event-triggered fault detection observer for LPV systems.

Algorithm 1. *For the given constants λ_1 to λ_4, a feasible solution for the problem of event-triggered fault detection observer design for LPV systems can be obtained by solving the following convex optimization problem*

$$\min_{P_i > 0, P_i^{'} > 0, G_i, G_i^{'}, \mathcal{G}_i, \forall i \in \{1, \ldots, n\}} \lambda_1 \gamma - \lambda_2 \beta + \lambda_3 \alpha_2 - \lambda_4 \alpha_3 \tag{32}$$

subject to (17) and (30).

Here, a procedure has been proposed for the co-design of a parameter-dependent observer gain and the event-triggering conditions for the corresponding fault detection observer of LPV systems.

Remark 3. *The values of λ_1 to λ_4 in Algorithm 1 can be selected by the designer to emphasize how much the objectives are important related to each other. The values of λ_1 and λ_2 are used to determine the disturbance attenuation and sensitivity of the residual signal to the fault signal. To reduce the data transmission between the sensor event detector and fault detection module, larger values for λ_3 and smaller values for λ_4 should be chosen.*

C. Residual evaluation criterion

Following the construction of the residual signal $r(k)$, the final step is to determine a threshold J_{th} and an evaluation function $J_r(k)$. Various evaluation functions can be considered. In this work, upper and lower threshold values are selected as

$$J_{\mathrm{th}}^u = \sup_{f=0,\omega} r(k), \quad J_{\mathrm{th}}^l = \inf_{f=0,\omega} r(k). \tag{33}$$

Considering the evaluation function as $J_r(k) = r(k)$, the occurrence of a fault can then be detected by using the following decision logic:

$$\text{If } r(k) > J_{\mathrm{th}}^u \quad \text{or} \quad r(k) < J_{\mathrm{th}}^l \Rightarrow f(k) \neq 0. \tag{34}$$

IV. Simulation Results

We consider a numerical example of an LPV system with a sensor fault that is described by the following state-space matrices

$$A(\theta_k) = \begin{bmatrix} 0.02 & 1 & 0 \\ 0 & 0.1 & 0 \\ 0 & 0 & 0.1 + \theta_k \end{bmatrix}, B_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, B_2 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix},$$
$$C = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}, \quad D_1 = 0.1, \quad D_2 = 1,$$

with $\theta_k \in [0, 0.5]$. The fault signal is simulated as a rectangular pulse with amplitude of 0.5 that is presented from $k = 10$ to $k = 30$ in the sensor. The disturbance signal injected to the system is chosen as a band-limited white noise with the power

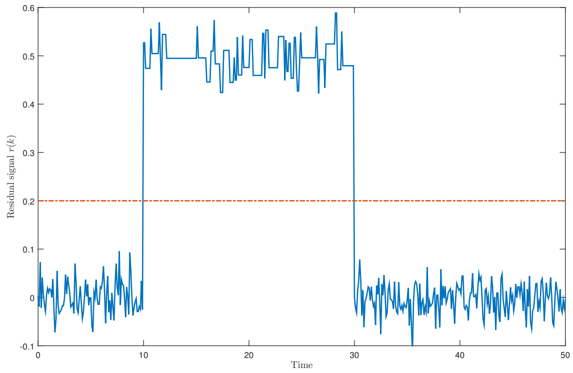

Fig. 2: Residual signal $r(k)$.

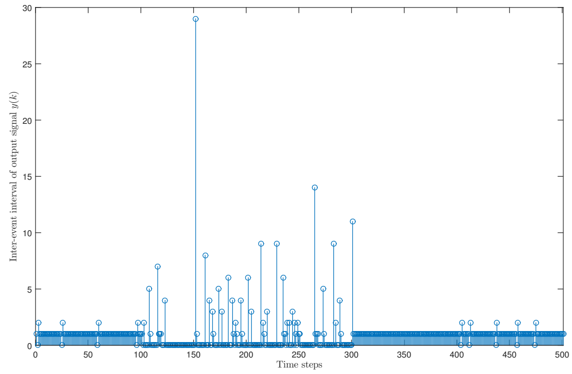

Fig. 4: Inter-event interval of the sensor event detector.

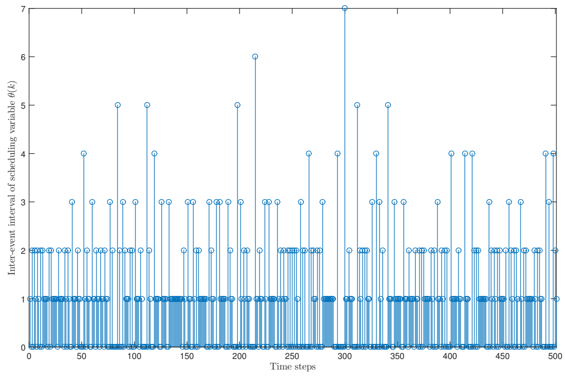

Fig. 3: Inter-event interval of the scheduling variable event detector.

of 0.001. Using Algorithm 1 with $\lambda_1 = \lambda_3 = \lambda_2 = \lambda_4 = 1$ and choosing $\delta_1 = 0.04$, the design parameters are obtained as $\beta = 0.27, \gamma = 3.2, \alpha_2 = 24.72$ and $\alpha_3 = 0.24$. Also, the thresholds corresponding to the healthy operation of the system are obtained as $J_{\text{th}}^u = 0.21$ and $J_{\text{th}}^l = -0.1$. Figure 2 shows the residual signal $r(k)$ that demonstrates that the fault signal $f(k)$ is readily detected using the proposed FD method. The inter-event intervals are shown in figures 3 and 4. The value of each stem shows the length of the time period between that event and the previous one which demonstrates a reduction of data transmission to 61.28% for scheduling variable and to 68.32% for the sensor data.

V. Conclusion

In this paper, the problem of event-triggered fault detection for discrete-time LPV systems is addressed. A parameter-dependent observer has been designed as a residual generator such that the information about the output signals and the scheduling variables are provided to the fault detection module only at triggering time instants. A multi-objective design formulation has been presented to satisfy the H_-/H_∞ performance indices, for which sufficient conditions have been obtained in the form of LMIs. The simulation results illustrate that the proposed fault detection approach and the event-triggering conditions are successful in detecting faults and at the same time reducing the amount of data sent to the fault detection module.

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